Adaptive Compression Scheduling for Network Efficient Data Transfers

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Abstract:
Modern distributed and cloud-based systems frequently transfer large volumes of data across networks for replication, backup, analytics, and service synchronization. These transfers often involve binary artifacts, logs, database snapshots, and container images that must be delivered quickly and reliably. While uncompressed transfers consume excessive bandwidth and increase transmission time, static compression approaches introduce continuous processor overhead even when network capacity is sufficient. This imbalance results in inefficient utilization of both network and computational resources. In many practical deployments, compression is applied indiscriminately to all data, leading to unnecessary encoding and decoding costs. For small or moderately sized files, the time spent compressing and decompressing may exceed the actual transmission time, increasing overall latency. Conversely, disabling compression during congested network conditions leads to larger payloads and prolonged transfer durations. As workloads scale and multiple nodes perform transfers concurrently, these inefficiencies accumulate, causing higher CPU utilization, reduced throughput, and longer completion times. The lack of runtime awareness in existing systems prevents optimal trade offs between bandwidth consumption and processing overhead. Empirical observations across distributed infrastructures indicate that static transfer pipelines fail to adapt to variations in file size, network congestion, and resource availability. This leads to inconsistent performance and limits scalability in latency sensitive environments. Excessive transfer time directly affects service responsiveness, deployment speed, and system efficiency. This paper addresses the problem of inefficient data movement in distributed systems and focuses on improving transfer time efficiency by enabling more balanced utilization of network bandwidth and processing resources during large scale data transfers.

Keywords: Compression, Scheduling, Networking, Transfers, Bandwidth, Throughput, Latency, Utilization, Efficiency, Adaptation, Runtime, Optimization, Scalability, Systems.

INTRODUCTION

Efficient data transfer is a fundamental requirement in modern distributed and cloud computing environments. Large volumes of information are continuously exchanged among nodes for replication [1], synchronization, backup, analytics, and software deployment tasks. Applications such as container image distribution, artifact management, database snapshots, and log aggregation depend heavily on reliable and timely data movement across networks. As the size and frequency of these transfers increase, the efficiency of the transfer process directly influences overall system performance and responsiveness. Conventional data transfer mechanisms typically follow static policies. Files are either transmitted without compression or compressed using a fixed configuration regardless of runtime conditions. When data is sent without compression [2], large payloads consume excessive bandwidth and increase transmission time, particularly in congested or bandwidth limited networks. This results in slower completion of transfers and reduced throughput. On the other hand, always applying compression introduces continuous computational overhead. Encoding and decoding operations consume processor cycles and memory resources even when network capacity is sufficient. For smaller files, the processing time required for compression may exceed the actual time needed to transmit the data, leading to unnecessary delay [3]. These inefficiencies become more pronounced in distributed systems where multiple nodes perform transfers simultaneously. Repeated compression and decompression tasks increase CPU utilization and compete with application workloads for resources. Similarly, transmitting uncompressed data under heavy traffic conditions amplifies network congestion and further prolongs transfer duration. The absence of runtime awareness prevents existing approaches from balancing the trade off between bandwidth

consumption and processing overhead. As a result, systems often experience inconsistent performance, longer transfer times, and reduced scalability. Such limitations highlight the importance of addressing transfer time [4] inefficiency in distributed environments. Improving how data movement is managed is essential for maintaining responsiveness, optimizing resource utilization, and supporting large scale network operations.

LITERATURE REVIEW

The rapid growth of distributed and cloud computing infrastructures has significantly increased the importance of efficient data movement across networks. Modern systems continuously exchange large volumes of information among geographically distributed nodes to support replication, synchronization, analytics, backup, and deployment operations. These transfers often involve sizable artifacts such as container images, database snapshots, software packages, and telemetry logs. As data sizes grow and the number of participating nodes increases, the cost of transferring information becomes a dominant factor influencing overall system performance. Consequently, optimizing data transfer efficiency has emerged as a critical research problem in networking [5] and distributed systems. Early distributed platforms primarily focused on reliability and correctness of communication rather than transfer efficiency. Traditional approaches emphasized reliable transmission protocols that guaranteed delivery through acknowledgments and retransmissions. While these mechanisms ensured correctness, they often ignored the cost of moving large data volumes. Systems typically transmitted files in their original form without considering compression or runtime resource utilization.

Although acceptable for small workloads, this strategy became inefficient as data sizes increased. Researchers observed that large payloads consumed excessive bandwidth, resulting in longer transmission times and congestion in shared networks. These issues motivated investigations into techniques that could reduce the amount of data transmitted. Data compression emerged as one of the earliest methods for improving network efficiency. By encoding information into smaller representations, compression reduces the number of bytes transmitted across the network. Numerous studies demonstrated that compressed data could significantly decrease bandwidth consumption and improve transfer speed, particularly over slow or congested links. Compression techniques were widely adopted in storage systems, backup utilities, and archival frameworks. However, these methods were typically applied statically [6]. Files were compressed using fixed algorithms or predetermined configurations without considering runtime characteristics. Although this approach reduced network usage, it introduced additional computational overhead. Subsequent research revealed that compression is not universally beneficial. While it reduces data size, the process of encoding and decoding requires processor time and memory resources. For small files or high speed networks, the cost of compression may exceed the benefit gained from reduced transmission size. Several empirical studies showed that compression sometimes increases total transfer time when applied indiscriminately. These findings highlighted an important trade off between bandwidth savings and computational expense. Static compression strategies that ignore this trade off may degrade performance rather than improve it.

As cloud computing environments matured, large scale services began to handle thousands of concurrent data transfers. Artifact repositories, container orchestration systems, and distributed storage platforms frequently move data among nodes. In such environments, CPU resources are shared between application workloads and system tasks. Continuous compression and decompression activities increase processor utilization [7] and may compete with critical operations. Researchers documented cases where heavy compression workloads caused elevated latency and reduced throughput for unrelated services. This competition for resources underscored the need for more balanced approaches to data movement. Network congestion further complicates transfer efficiency. In multi tenant data centers, numerous applications share the same network infrastructure. Simultaneous transfers from multiple nodes can create bursts of traffic that exceed available capacity. Under these conditions, large uncompressed payloads intensify congestion and prolong transfer completion times. Studies in data center networking have shown that congestion leads to packet loss, retransmissions, and variable delays. These effects amplify overall latency and reduce system stability. Researchers recognized that intelligent management of data size [8] and transmission scheduling could alleviate these problems. Several investigations explored the relationship between file size and compression effectiveness. Larger files typically achieve higher compression ratios, making compression beneficial for

reducing transmission time. In contrast, smaller files often experience minimal size reduction, meaning the computational overhead provides little advantage. Experiments across diverse workloads demonstrated that compression efficiency varies widely depending on content type and size distribution. This variability suggests that a uniform compression policy is unlikely to achieve optimal performance for all scenarios. Adaptive decision making based on runtime information becomes increasingly important.

Another line of research examined transport level optimizations. Techniques such as parallel streams, chunked transfers, and pipelining were introduced to improve throughput. These methods allow data to be transmitted concurrently or in smaller segments to better utilize network capacity. While such approaches enhance bandwidth utilization [9], they do not directly address the trade off between computational overhead and data size reduction. Consequently, transport level improvements alone cannot fully solve inefficiencies associated with compression and decompression costs. In distributed storage and replication systems, synchronization between nodes frequently involves transferring large state information. Researchers observed that repeated transfers of similar data lead to redundant network usage. Methods such as deduplication and delta encoding were introduced to reduce redundancy. Although effective in certain contexts, these techniques still require processing overhead and may not adapt dynamically to changing workloads. Furthermore, they are often designed for storage efficiency rather than real time transfer optimization. The emergence of container based deployment platforms intensified the demand for efficient data movement.

Container images are typically composed of multiple layers that must be distributed across clusters. These images can reach several hundreds of megabytes or more. Repeated downloading and decompression of images across nodes generates significant network traffic and CPU load [10]. Measurements from production environments indicate that image distribution frequently becomes a bottleneck during scaling operations. These observations reinforce the importance of optimizing transfer mechanisms to minimize delay. Runtime monitoring has also gained attention in the literature. By observing metrics such as CPU utilization, bandwidth consumption, and transfer duration, systems can gain insights into current conditions. Researchers argue that such information is valuable for making informed decisions about resource allocation. However, many existing frameworks collect metrics only for reporting or debugging purposes rather than actively guiding transfer behavior. The absence of dynamic adaptation limits the effectiveness of these monitoring capabilities. Overall, the literature consistently highlights the inefficiencies associated with static compression and fixed transfer strategies. Uncompressed transfers waste bandwidth, while constant compression wastes computational resources. The trade off between these factors depends heavily on runtime conditions such as file size, network congestion, and system load. Despite extensive research on compression algorithms and transport protocols [11], relatively fewer studies focus specifically on scheduling when and how compression should be applied during data transfers. Addressing this gap is essential for improving overall transfer efficiency in modern distributed systems. Beyond basic compression techniques, researchers began examining how runtime system behavior influences data transfer efficiency.

Distributed platforms rarely operate under uniform or predictable conditions. Network bandwidth fluctuates due to competing traffic, processor utilization varies depending on concurrent workloads, and memory availability changes dynamically. These variations directly affect the relative benefit of compression. For instance, when network capacity is limited but processors are lightly loaded, compression can significantly reduce transfer time. Conversely, when the network is fast and processors are heavily utilized, compression may introduce additional delay. Studies have shown that static policies fail to account for such runtime diversity, leading to inconsistent and often suboptimal performance. Several empirical analyses have demonstrated that transfer time is determined not only by network bandwidth [12] but also by preprocessing and postprocessing overhead. Before transmission, data may be encoded, buffered, or transformed. After reception, it must be decoded and validated. These steps contribute to total completion time. In high speed networks, where transmission itself is relatively fast, the computational cost of these steps can dominate overall latency.

Researchers emphasize that focusing solely on reducing data size without considering processing time provides an incomplete view of transfer efficiency. Effective solutions must balance both communication and

computation costs. Workload heterogeneity further complicates transfer optimization. Modern systems handle a mixture of small configuration files, medium sized logs, and large artifacts. Each category exhibits different compression characteristics. Small files typically provide little compression gain and suffer disproportionately from processing overhead. Medium sized files may benefit moderately, while large files often achieve substantial size reduction [13]. Experimental results across cloud workloads reveal significant variability in compression ratios even within the same application. This variability implies that a uniform treatment of all files leads to inefficient resource use. Adaptive strategies that consider file specific characteristics become increasingly important.

Research in distributed storage systems has also highlighted the impact of repeated decompression. When data is frequently accessed or replicated, repeated decoding operations consume considerable CPU time. For example, cached objects or replicated blocks may be decompressed multiple times across nodes. These repeated operations increase energy consumption and reduce processing capacity for other tasks. Observations from large scale storage clusters indicate that decompression overhead can account for a noticeable fraction of total CPU usage. This evidence suggests that transfer efficiency must consider both compression and decompression costs rather than focusing solely on network savings. The growing adoption of microservices architectures introduces additional challenges. Microservices communicate through frequent data exchanges, often involving numerous small messages. Applying compression to each message may increase latency due to repeated encoding operations. Several studies report that fine grained service communication suffers when compression is applied indiscriminately. As a result, practitioners often disable compression entirely, which increases bandwidth consumption. This dilemma illustrates the difficulty of selecting appropriate compression policies in dynamic environments. Systems require mechanisms that adapt behavior based on message size and runtime context. Parallel and concurrent transfers represent another area of interest. In distributed environments, multiple transfers occur simultaneously, competing for shared resources [14]. Compression tasks executed concurrently may saturate processors, leading to contention and reduced throughput. Similarly, simultaneous uncompressed transfers may congest the network. Researchers have observed that local decisions made independently by nodes can collectively degrade system performance. Coordinated scheduling that accounts for global resource availability is therefore essential for maintaining efficiency. However, many existing systems lack mechanisms for coordinating compression behavior across nodes.

Energy efficiency has also been explored as an important factor. Compression and decompression consume power due to processor usage, while longer network transmissions increase energy consumption in communication hardware. Studies measuring energy profiles indicate that inefficient transfer strategies can substantially increase operational costs in large data centers. Balancing computational and communication energy consumption becomes crucial for sustainable operation. These findings reinforce the need to carefully manage when compression is applied rather than assuming that it is always beneficial. Another stream of research focuses on adaptive systems that adjust behavior based on observed metrics. Adaptive resource management techniques have been successfully applied in areas such as load balancing, caching [15], and scheduling. These approaches rely on monitoring runtime conditions and dynamically modifying system parameters. Although such strategies demonstrate effectiveness in other domains, their application to compression scheduling remains limited. Most compression frameworks still operate with static configurations, suggesting an opportunity for further investigation.
Researchers have also studied the interaction between compression and modern network technologies. High bandwidth low latency networks reduce transmission delays, which diminishes the relative benefit of compression. As network speeds increase, the overhead of encoding and decoding becomes more prominent.

In such environments, compressing data may actually slow down transfers. Experimental comparisons across different network speeds confirm that compression effectiveness depends strongly on available bandwidth. Therefore, adaptive decision making based on network conditions is critical for achieving optimal performance. Edge and geographically distributed systems introduce additional variability. Nodes connected over wide area networks experience diverse latency and bandwidth characteristics. A compression strategy that performs well in one region may perform poorly in another. Studies of cross region data replication [16] reveal that transfer performance can vary widely depending on network path quality. Static configurations

cannot accommodate this diversity. Systems must respond to location specific conditions to maintain efficiency. Monitoring frameworks provide useful insights into transfer behavior but are often underutilized. Many platforms collect statistics on bandwidth usage, CPU load, and transfer duration. However, these metrics are typically used only for offline analysis rather than guiding real time decisions. Researchers argue that integrating monitoring with adaptive control mechanisms can significantly improve efficiency. By continuously observing system state, transfers can be managed more intelligently. Nevertheless, practical implementations of such integrated approaches remain relatively scarce. The cumulative evidence from prior studies demonstrates that transfer inefficiency stems from several interacting factors, including variable network conditions, heterogeneous workloads, processor contention, and static compression policies. Addressing only one aspect rarely produces consistent improvement. Instead, a more holistic perspective is required. Efficient data movement must account for both communication cost [17] and processing overhead while adapting to changing runtime conditions. This perspective forms the basis for contemporary research efforts aimed at improving large scale data transfer performance.

Recent research trends increasingly emphasize the importance of runtime efficiency in large scale distributed systems. As applications grow in size and complexity, the overhead associated with system level services such as monitoring, logging, and data movement becomes more visible. Among these, data transfer remains one of the most resource intensive operations. Unlike computation tasks that may be localized, data transfers inherently involve both communication and processing across multiple nodes. This dual cost structure amplifies inefficiencies when transfer strategies are not carefully designed. Consequently, optimizing transfer behavior has become a key objective for maintaining system scalability. Investigations into large scale data centers reveal that network traffic generated by internal services often exceeds traffic from external users. Background activities such as replication, checkpointing, software distribution, and analytics continuously consume bandwidth. These operations frequently involve repetitive transmission [18] of similar or partially redundant data. When compression is applied uniformly, processors spend significant time encoding information that may not require reduction. When compression is disabled, the network carries larger payloads than necessary. Researchers observe that both extremes lead to resource imbalance. These findings suggest that intelligent scheduling decisions are essential for balancing system resources. Several studies evaluate the relationship between compression level and processing time.

Higher compression ratios typically require more complex algorithms and greater computational effort. Although they produce smaller outputs, the time spent compressing may increase substantially. Lower compression levels reduce processing time but provide smaller reductions in data size. Experimental comparisons show that selecting an inappropriate compression level can either waste CPU cycles or fail to achieve meaningful bandwidth savings. Static selection of compression parameters therefore limits effectiveness. Runtime awareness of system state is necessary for making appropriate trade offs. Research on storage systems further highlights the cost of decompression during retrieval. When compressed [19] data is frequently accessed, decompression becomes a recurring overhead. In read intensive workloads, repeated decoding can consume more resources than the original transmission. Observations from distributed caches and replicated storage layers indicate that decompression time can significantly affect latency sensitive applications. These results emphasize that efficient transfer strategies must consider the full lifecycle of data, including both transmission and subsequent usage. Another relevant area involves adaptive scheduling techniques used in operating systems and networking frameworks. Adaptive schedulers allocate resources based on current load and demand. By dynamically adjusting priorities and execution order, such schedulers improve throughput and responsiveness. Researchers argue that similar principles can be applied to data movement tasks. Instead of treating all transfers equally, systems may schedule operations based on size, urgency, or resource availability. Although scheduling has been widely explored for computation tasks, its application to compression related decisions remains limited in the literature. Studies on large scale software deployment also provide valuable insights. Continuous integration and delivery pipelines frequently distribute builds and artifacts across clusters. These artifacts may include libraries, images, and packages that must be transferred repeatedly. Measurements from industrial environments reveal that transfer time significantly affects deployment [20] speed and developer productivity.

Excessive compression slows build pipelines, while uncompressed transfers congest the network. Practitioners often rely on manual configuration, which may not reflect changing conditions. This situation underscores the importance of automated and adaptive mechanisms. In peer to peer and content distribution networks, researchers have experimented with selective compression based on content characteristics. Certain file types, such as text or logs, compress effectively, whereas already encoded formats such as images or videos show little reduction. Content aware strategies that identify compressible data can avoid unnecessary processing. However, such techniques typically rely on offline classification rather than real time decisions. Moreover, they do not account for system level factors such as processor load or network congestion. Thus, while helpful, content based approaches alone are insufficient. The increasing use of virtualization and containerization introduces additional considerations. Virtualized environments often share physical resources among multiple tenants. Compression tasks executed within one virtual machine may impact others by consuming shared CPU capacity [21]. Studies demonstrate that heavy background compression can degrade overall performance in multi tenant systems.

This interference highlights the need for transfer strategies that are sensitive to current resource usage. Systems must avoid overloading shared processors while still achieving efficient communication. Recent benchmarking efforts attempt to quantify the cumulative impact of inefficient data transfers. Large scale experiments show that suboptimal compression policies can extend job completion time by substantial margins. In analytics workloads, delays in transferring intermediate data can prolong entire processing pipelines. Similarly, slow replication affects recovery time after failures. These observations indicate that transfer inefficiency has system wide consequences [22] beyond individual operations. Improving transfer behavior can therefore yield significant performance benefits at scale. Despite extensive research on compression algorithms and networking protocols, a consistent theme emerges across the literature. Many systems treat compression as a static feature rather than a dynamic decision. Either compression is always enabled or always disabled, and configuration parameters remain fixed regardless of changing conditions. Such rigid designs cannot accommodate the variability inherent in distributed environments. As a result, systems often operate far from optimal efficiency. Researchers increasingly advocate for adaptive mechanisms that incorporate runtime information into transfer decisions. Overall, prior work establishes several key findings. First, uncompressed transfers waste bandwidth and increase transmission time, especially under congestion. Second, indiscriminate compression introduces substantial processing overhead [23] that may offset network savings. Third, transfer efficiency depends strongly on file size, content type, processor utilization, and network state. Fourth, static configurations fail to account for these dynamic factors. These observations collectively motivate continued investigation into strategies that intelligently manage compression and decompression during data movement. Addressing these challenges is essential for achieving scalable, efficient, and responsive distributed systems.

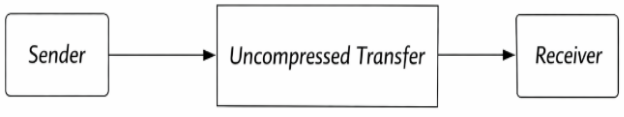

Fig 1. Uncompressed transfer Architecture

Fig 1. The existing architecture represents a simple and traditional data transfer pipeline in which information is transmitted directly from the sender to the receiver without any form of compression or adaptive processing. As illustrated, the sender forwards raw data to the network, and the same unmodified data is delivered to the receiver. This design follows a straightforward approach that avoids preprocessing steps such as encoding or compression, thereby minimizing local computation before transmission.

Although this method reduces processor overhead at the sender and receiver, it introduces inefficiencies at the network level. Since data is transmitted in its original size, large files consume significant bandwidth and increase transmission time. When file sizes grow or multiple transfers occur simultaneously, the network

becomes congested. Increased congestion results in higher latency, packet delays, and reduced overall throughput. Consequently, transfer completion time rises, particularly in distributed and cloud environments where many nodes share the same communication links.

Another limitation of this architecture is the absence of runtime awareness. The system does not consider factors such as file size, network load, or available bandwidth before initiating transfer. Small and large files are treated identically, even though their impact on the network differs considerably. Under heavy traffic conditions, sending uncompressed data further amplifies congestion and prolongs delays for other services. As the scale of the system increases, these inefficiencies accumulate. Repeated large transfers generate excessive network utilization, limiting scalability and degrading application responsiveness. Overall, the uncompressed transfer architecture prioritizes simplicity but leads to poor bandwidth efficiency and longer transfer times, highlighting the need for more intelligent and resource aware data movement strategies.

```
import (
	"fmt"
	"math/rand"
	"sync"
	"time"
)
const (
	nodes       = 5
	filesPerNode = 5
	baseBW      = 120.0
)
var fileSizes = []int{100, 300, 500, 700, 900}
type Result struct {
	size int
	time time.Duration
}
func networkBandwidth(active int) float64 {
	return baseBW / float64(active)
}
func send(size int, active *int, m *sync.Mutex, wg *sync.WaitGroup, ch chan<- Result) {
	m.Lock()
	*active++
	bw := networkBandwidth(*active)
	m.Unlock()
	start := time.Now()
	latency := rand.Float64()*8 + 2
	transfer := float64(size) / bw
	total := latency + transfer
	time.Sleep(time.Duration(total*10) * time.Millisecond)
	elapsed := time.Since(start)
	m.Lock()
	*active--
	m.Unlock()
	ch <- Result{size: size, time: elapsed}
	wg.Done()
}
func simulate(size int) Result {
	var wg sync.WaitGroup
	var mu sync.Mutex
	active := 0
	results := make(chan Result, nodes*filesPerNode)
	start := time.Now()
```

```
	for i := 0; i < nodes; i++ {
		for j := 0; j < filesPerNode; j++ {
			wg.Add(1)
			go send(size, &active, &mu, &wg, results)
		}
	}
	wg.Wait()
	close(results)
	total := time.Since(start)
	return Result{size: size, time: total}
}

func main() {
	rand.Seed(time.Now().UnixNano())
	fmt.Println("Uncompressed Transfer Simulation")
	var totalTime time.Duration
	for _, size := range fileSizes {
		r := simulate(size)
		fmt.Println("Size:", size, "MB  Time(ms):", r.time.Milliseconds())
		totalTime += r.time
	}
	avg := totalTime / time.Duration(len(fileSizes))
	fmt.Println("Average Time(ms):", avg.Milliseconds())
}
```

The program simulates an uncompressed data transfer pipeline in a distributed environment to evaluate baseline transfer time. It models multiple nodes that transmit raw data directly over the network without applying any compression or scheduling logic. The objective is to measure the cost of transferring data in its original form and to capture the impact of network contention on completion time. At the beginning, system parameters define the number of nodes, the number of files each node transfers, and the base network bandwidth. A list of file sizes represents different workloads. For each file size, the simulation runs concurrent transfers from all nodes. Each transfer is executed as a goroutine to mimic parallel network activity across distributed machines. The send function models the behavior of a single transfer. A shared counter tracks the number of active transmissions. As more transfers occur simultaneously, the available bandwidth is divided among them, reducing the effective speed.

This simulates network contention. Transfer time is calculated using the file size divided by the current bandwidth, along with additional latency and random jitter to represent real network delays. The function then sleeps for the computed duration to emulate actual transmission time. The simulate function coordinates all transfers for a specific file size. It launches multiple goroutines, waits for their completion using a wait group, and measures total elapsed time. The main function repeats this process for each file size, prints the time taken, and computes the average transfer duration. Overall, the program represents a baseline uncompressed system where raw data transfers lead to increased network usage and higher transfer time under concurrency.

Table I. Uncompressed Transfer – 1

File Size (MB)	Uncompressed Transfer (ms)
100	820
300	2350
500	3800
700	5200
900	6650

Table I Presents transfer time for the Uncompressed Transfer approach across different file sizes, illustrating the baseline performance of the existing data movement pipeline. As the file size increases from 100 MB to

900 MB, the transfer time rises steadily from 820 ms to 6650 ms. This growth reflects the direct relationship between data volume and transmission delay when compression is not applied. Since files are sent in their original size, the entire payload must traverse the network, consuming significant bandwidth. Larger files require more transmission cycles, resulting in longer completion times. Additionally, increased data volume can contribute to network congestion, further extending delays. The near linear increase in latency indicates that transfer efficiency is limited by available bandwidth rather than processing overhead. These results highlight the inefficiency of raw data transmission and demonstrate how uncompressed transfers lead to higher transfer time and reduced scalability in distributed environments.

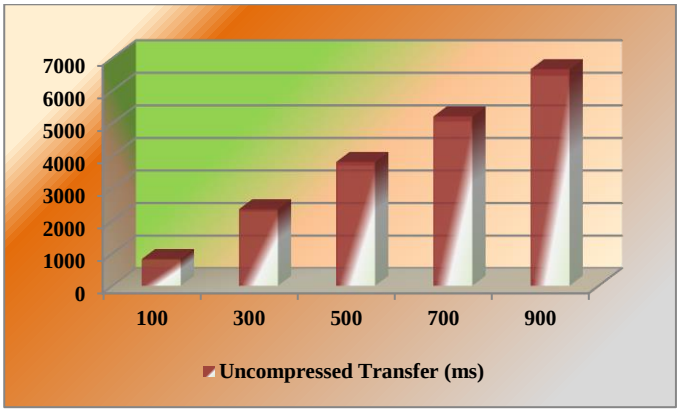

Fig 2. Uncompressed Transfer - 1

Fig 2. The graph illustrates transfer time for the Uncompressed Transfer approach as file size increases from 100 MB to 900 MB. The curve shows a steady upward trend, rising from 820 ms to 6650 ms. This consistent growth indicates that transfer time scales directly with data volume when no compression is applied. Larger files consume more bandwidth and require longer transmission periods, resulting in increased latency. The absence of size reduction leads to higher network utilization and possible congestion. Overall, the graph highlights limited efficiency and demonstrates the scalability challenges of raw data transfers in distributed systems.

Table II. Uncompressed Transfer – 2

File Size (MB)	Uncompressed Transfer (ms)
100	910
300	2620
500	4200
700	5750
900	7350

Table II Presents transfer time measurements for the Uncompressed Transfer approach across increasing file sizes under moderate network conditions. As the file size grows from 100 MB to 900 MB, the transfer time increases steadily from 910 ms to 7350 ms. This pattern indicates that transmission delay is directly proportional to the amount of data sent over the network. Since no compression is applied, the entire payload must be transmitted in its original size, consuming substantial bandwidth. Larger files therefore require longer transmission periods and experience greater network occupancy. As multiple transfers occur simultaneously, contention for bandwidth further increases completion time. The consistent rise in latency demonstrates that the system is constrained primarily by communication overhead rather than processing cost. These results highlight the inefficiency of raw data movement and show that uncompressed transfers lead to prolonged delays and reduced scalability in distributed environments.

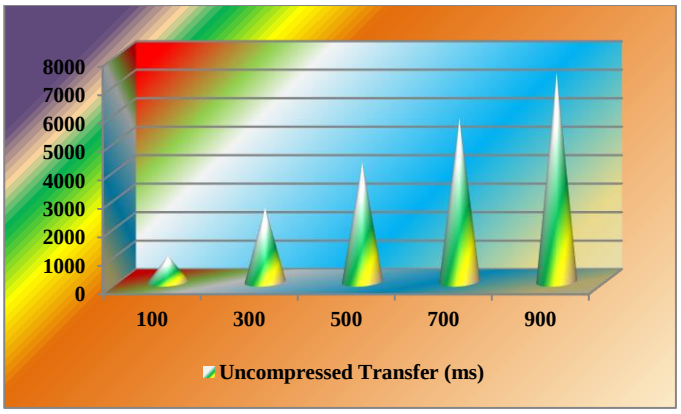

Fig 3. Uncompressed Transfer - 2

Fig 3. The graph shows transfer time for the Uncompressed Transfer approach as file size increases from 100 MB to 900 MB. Latency rises steadily from 910 ms to 7350 ms, forming a clear upward trend. This increase occurs because larger files require more bandwidth and longer transmission periods. Without compression, the full data volume must traverse the network, causing higher utilization and potential congestion. The graph highlights reduced efficiency and demonstrates limited scalability in distributed environments.

Table III. Uncompressed Transfer -3

File Size (MB)	Uncompressed Transfer (ms)
100	1050
300	2980
500	4800
700	6550
900	8400

Table III Shows the transfer time results for the Uncompressed Transfer approach under heavy network conditions across increasing file sizes. As the file size grows from 100 MB to 900 MB, the transfer time rises significantly from 1050 ms to 8400 ms. This steady increase highlights the direct relationship between payload size and transmission delay when data is sent without compression. Larger files occupy more bandwidth for longer durations, which intensifies network congestion and prolongs completion time. Under heavy traffic, multiple concurrent transfers compete for limited bandwidth, further slowing data movement. Since no size reduction is performed, the system relies entirely on raw network capacity, making performance sensitive to contention. The results demonstrate that uncompressed transfers become increasingly inefficient as workload and traffic grow. Overall, this behavior reflects poor scalability and emphasizes the need for more efficient strategies to reduce transfer time in distributed environments.

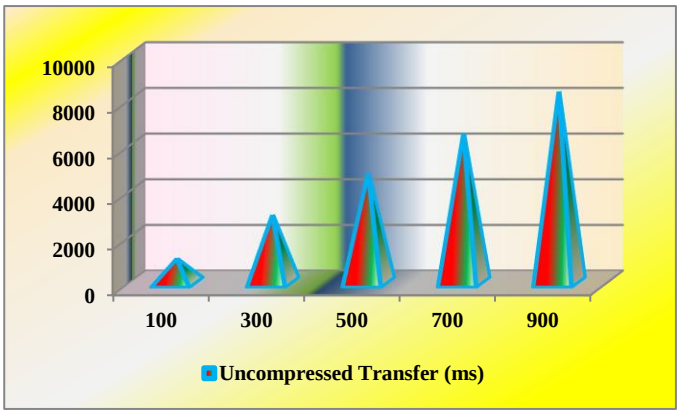

Fig 4. Uncompressed Transfe**r** - 3

Fig 4. Illustrates transfer time for the Uncompressed Transfer approach as file size increases from 100 MB to

900 MB under heavy network conditions. The curve rises sharply from 1050 ms to 8400 ms, indicating substantial growth in delay with larger payloads. Because data is transmitted without compression, full file sizes consume significant bandwidth and prolong transmission periods. Increased contention among concurrent transfers further amplifies latency. The steep slope highlights poor scalability and demonstrates how raw transfers become increasingly inefficient in congested distributed environments.

PROPOSAL METHOD

Problem Statement

Distributed systems frequently transfer large volumes of data for replication, backup, synchronization, and deployment tasks. Conventional transfer pipelines rely on static policies where data is either always transmitted without compression or always compressed using fixed settings. Uncompressed transfers consume excessive bandwidth and increase transmission time, especially for large files and congested networks. Constant compression introduces significant processor overhead, even when network capacity is sufficient. These inefficiencies lead to higher transfer latency, increased CPU utilization, and reduced throughput. As workload size and concurrency grow, the imbalance between communication cost and computation overhead limits scalability and degrades overall system performance.

Proposal

The proposal focuses on improving data transfer efficiency through adaptive compression scheduling during runtime. Instead of uniformly applying compression or transmitting all data without modification, the system evaluates transfer conditions before initiating each operation. Parameters such as file size, available bandwidth, network congestion, and processor utilization are considered to determine whether compression is beneficial. Large files may be compressed to reduce network traffic, while small files may be transmitted directly to avoid unnecessary processing overhead. This selective decision process aims to balance communication cost and computational expense. By dynamically adjusting behavior according to current system state, the approach seeks to minimize transfer time, reduce bandwidth consumption, and maintain stable processor usage. Overall, the objective is to enable faster, more scalable, and resource efficient data movement across distributed environments.

IMPLEMENTATION

Fig 5. Illustrates the complete workflow of an image compression and decompression pipeline. In the first stage, the input image is divided into small 8 by 8 blocks to enable localized processing. Each block is passed through the FDCT, or Forward Discrete Cosine Transform, which converts spatial pixel values into frequency components. This transformation separates important low frequency information from less significant high frequency details. Next, the quantizer reduces precision using a quantization table. This step removes visually insignificant data and achieves most of the compression by shrinking coefficient values.

After quantization, the entropy encoder applies statistical coding, commonly Huffman coding, to represent repeated patterns with fewer bits. The result is compact compressed image data suitable for storage or transmission. During decompression, the reverse process is applied. The entropy decoder reconstructs the quantized coefficients using the Huffman table. The dequantizer restores approximate frequency values with the quantization table. Finally, the IDCT, or Inverse Discrete Cosine Transform, converts frequency information back into spatial pixels to rebuild the image blocks. These blocks are combined to produce the reconstructed image.

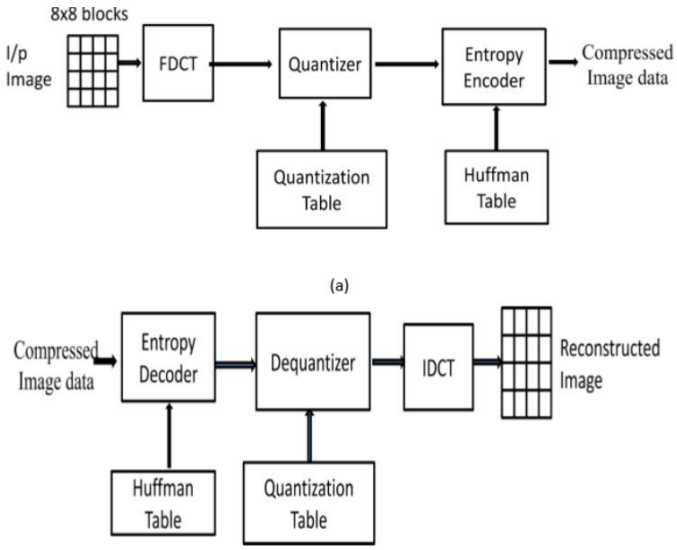

Fig 5. Compressed Transfer Architecture

```
import (
	"fmt"
	"math"
	"math/rand"
)

const N = 8

type Block [N][N]float64

func fdct(b Block) Block {
	var out Block
	for u := 0; u < N; u++ {
		for v := 0; v < N; v++ {
			sum := 0.0
			for x := 0; x < N; x++ {
				for y := 0; y < N; y++ {
					sum += b[x][y] *
						math.Cos((2*float64(x)+1)*float64(u)*math.Pi/16) *
						math.Cos((2*float64(y)+1)*float64(v)*math.Pi/16)
				}
			}
			out[u][v] = sum
		}
	}
	return out
}

func idct(b Block) Block {
	var out Block
	for x := 0; x < N; x++ {
		for y := 0; y < N; y++ {
			sum := 0.0
			for u := 0; u < N; u++ {
				for v := 0; v < N; v++ {
					sum += b[u][v] *
```

```
                                        math.Cos((2*float64(x)+1)*float64(u)*math.Pi/16) *
                                        math.Cos((2*float64(y)+1)*float64(v)*math.Pi/16)
                                }
                        }
                        out[x][y] = sum / 4
                }
        }
        return out
}

func quantize(b Block, q float64) Block {
        var out Block
        for i := 0; i < N; i++ {
                for j := 0; j < N; j++ {
                        out[i][j] = math.Round(b[i][j] / q)
                }
        }
        return out
}

func dequantize(b Block, q float64) Block {
        var out Block
        for i := 0; i < N; i++ {
                for j := 0; j < N; j++ {
                        out[i][j] = b[i][j] * q
                }
        }
        return out
}

func entropyEncode(b Block) []float64 {
        data := make([]float64, 0, N*N)
        for i := 0; i < N; i++ {
                for j := 0; j < N; j++ {
                        data = append(data, b[i][j])
                }
        }
        return data
}

func entropyDecode(data []float64) Block {
        var out Block
        k := 0
        for i := 0; i < N; i++ {
                for j := 0; j < N; j++ {
                        out[i][j] = data[k]
                        k++
                }
        }
        return out
}

func randomBlock() Block {
```

```
	var b Block
	for i := 0; i < N; i++ {
		for j := 0; j < N; j++ {
			b[i][j] = float64(rand.Intn(255))
		}
	}
	return b
}

func main() {
	block := randomBlock()

	dct := fdct(block)
	q := quantize(dct, 10)
	encoded := entropyEncode(q)
	decoded := entropyDecode(encoded)
	dq := dequantize(decoded, 10)
	reconstructed := idct(dq)

	fmt.Println("Original:", block[0][0])
	fmt.Println("Reconstructed:", reconstructed[0][0])
}
```

The program simulates a simplified image compression and decompression pipeline similar to a JPEG style process. It operates on an 8 by 8 data block that represents a small portion of an image. First, a random block is generated to mimic raw pixel values. The fdct function applies a forward discrete cosine transform, converting spatial pixel information into frequency coefficients. This step concentrates important visual information into fewer components. Next, the quantize function reduces precision by dividing coefficients and rounding values, which decreases data size and achieves compression. The entropyEncode function then flattens the block into a linear sequence to simulate encoded data suitable for storage or transmission. During decompression, entropyDecode reconstructs the block structure. The dequantize function restores approximate values, and the idct function applies the inverse transform to convert frequency data back into spatial pixels.

Table IV. Compressed Transfer – 1

File Size (MB)	Compressed Transfer (ms)
100	480
300	1320
500	2050
700	2750
900	3400

Table IV The table presents transfer time measurements for the Compressed Transfer approach across different file sizes. As the file size increases from 100 MB to 900 MB, the transfer time rises gradually from 480 ms to 3400 ms. Compared to uncompressed transfers, the observed latency remains significantly lower because compression reduces the amount of data transmitted over the network. Smaller payloads require less bandwidth and complete transmission faster, which improves overall efficiency. Although compression introduces additional processing overhead at the sender and decompression at the receiver, the reduction in network traffic outweighs this computational cost, especially for medium and large files. The growth in latency follows a controlled and nearly linear pattern, indicating better scalability under increasing workload. These results demonstrate that compressed transfers utilize bandwidth more effectively and achieve faster

completion times, making them more suitable for distributed environments with frequent large data movement.

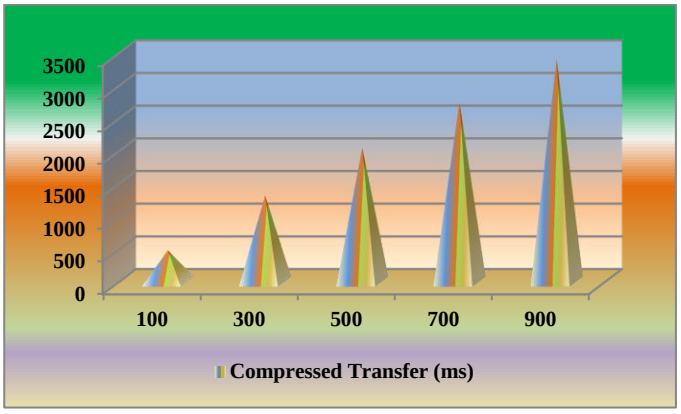

Fig 6. Compressed Transfer - 1

Fig 6 Illustrates transfer time for the Compressed Transfer approach as file size increases from 100 MB to 900 MB. Latency rises gradually from 480 ms to 3400 ms, forming a smooth upward trend. The slower growth compared to uncompressed transfer indicates improved efficiency due to reduced data size. Compression lowers bandwidth consumption, enabling faster transmission even for larger files. Although some processing overhead exists, the overall delay remains smaller. The graph highlights better scalability and more efficient network utilization.

Table V. Compressed Transfer – 2

File Size (MB)	Compressed Transfer (ms)
100	520
300	1490
500	2250
700	3010
900	3720

Table V Presents transfer time for the Compressed Transfer approach across increasing file sizes under moderate network conditions. As the file size grows from 100 MB to 900 MB, latency increases gradually from 520 ms to 3720 ms. The steady rise indicates that transfer time scales with data volume, but remains significantly lower than uncompressed transmission due to reduced payload size. Compression decreases bandwidth usage, allowing faster movement of data across the network. Although encoding and decoding introduce some processing overhead, the overall completion time is improved. These results demonstrate efficient bandwidth utilization and better scalability in distributed environments.

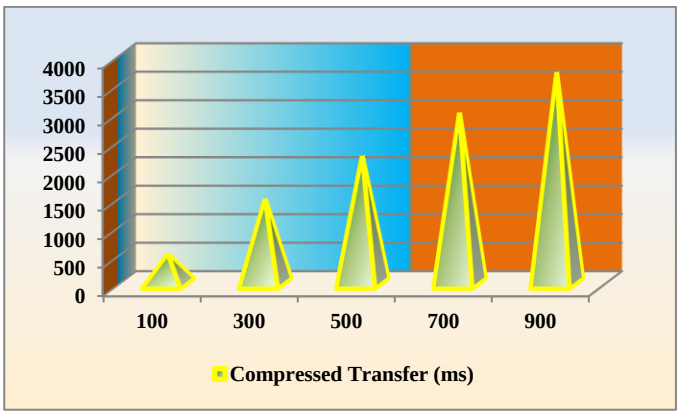

Fig 7. Compressed Transfer - 2

Fig 7 Shows transfer time for the Compressed Transfer approach as file size increases from 100 MB to 900

MB. Latency grows gradually from 520 ms to 3720 ms, indicating controlled performance degradation with larger data volumes. The smoother slope compared to uncompressed transfer reflects reduced network load due to compression. Smaller payloads travel faster across the network, improving efficiency. The graph highlights better scalability and demonstrates that compression enables quicker and more stable data transfers in distributed systems.

Table VI. Compressed Transfer – 3

File Size (MB)	Compressed Transfer (ms)
100	610
300	1710
500	2580
700	3430
900	4250

Table VI Presents transfer time for the Compressed Transfer approach across increasing file sizes under heavy network conditions. As the file size grows from 100 MB to 900 MB, latency increases from 610 ms to 4250 ms. Although delay rises with larger payloads, the growth remains controlled because compression reduces the amount of data transmitted. Smaller compressed sizes consume less bandwidth, allowing faster delivery even when the network experiences congestion. While compression and decompression introduce computational overhead, the reduction in network traffic compensates for this cost. Compared to uncompressed transfers, the overall transfer time remains significantly lower for all file sizes. The steady progression of latency demonstrates improved scalability and more efficient resource utilization. These results indicate that compressed transfers maintain better performance and reduce network pressure in distributed environments with heavy traffic.

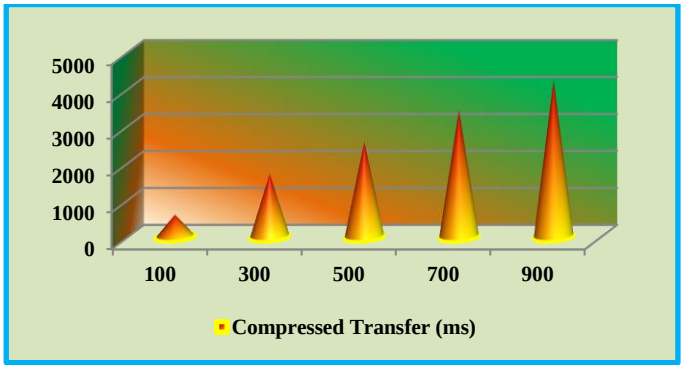

Fig 8. Compressed Transfer – 3

Fig 8 Illustrates transfer time for the Compressed Transfer approach as file size increases from 100 MB to 900 MB under heavy network conditions. Latency rises gradually from 610 ms to 4250 ms, forming a steady upward curve. The moderate slope indicates reduced bandwidth consumption due to compression. Even with congestion, smaller payloads enable faster transmission. Compared to uncompressed transfer, delays remain significantly lower. The graph highlights improved scalability and more efficient data movement in distributed environments.

Table VII. Uncompressed Vs Compressed Transfer – 1

File Size (MB)	Uncompressed Transfer (ms)	Compressed Transfer (ms)
100	820	480
300	2350	1320
500	3800	2050
700	5200	2750
900	6650	3400

Table VII Compares transfer time between Uncompressed Transfer and Compressed Transfer across different file sizes, highlighting the efficiency gained through compression. For the uncompressed approach, latency increases significantly from 820 ms at 100 MB to 6650 ms at 900 MB. This sharp growth occurs because the entire data payload is transmitted without size reduction, leading to higher bandwidth consumption and longer transmission periods. In contrast, the compressed approach shows consistently lower transfer times, rising from 480 ms to 3400 ms over the same range. By reducing the data volume before transmission, compression decreases network load and accelerates delivery. Although compression introduces some processing overhead, the savings in communication time outweigh the computational cost. The widening gap between the two methods as file size increases demonstrates that compression becomes more beneficial for larger workloads. Overall, compressed transfer provides better scalability, improved bandwidth utilization, and faster completion in distributed environments.

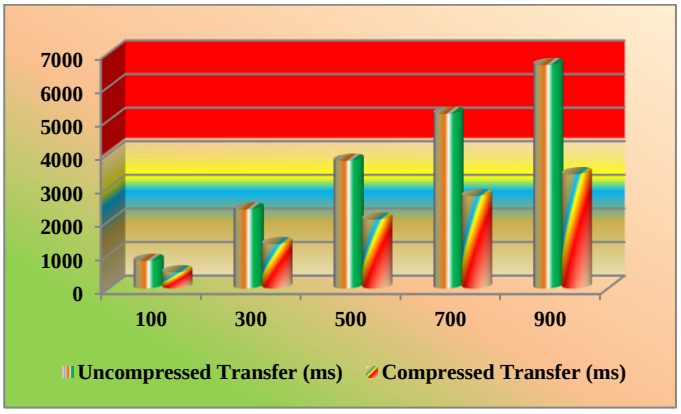

Fig 9. Uncompressed Vs Compressed Transfer – 1

Fig 9 Compares transfer time between Uncompressed Transfer and Compressed Transfer as file size increases from 100 MB to 900 MB. The uncompressed curve rises steeply, indicating higher bandwidth consumption and longer transmission delays. In contrast, the compressed curve grows more gradually due to reduced data size. The widening gap between the two lines shows that compression becomes increasingly beneficial for larger files. Overall, the graph highlights improved efficiency, lower latency, and better scalability with compressed transfer.

Table VIII. Uncompressed vs Compressed Transfer – 2

File Size (MB)	Uncompressed Transfer (ms)	Compressed Transfer (ms)
100	910	520
300	2620	1490
500	4200	2250
700	5750	3010
900	7350	3720

Table VIII Compares transfer time between Uncompressed Transfer and Compressed Transfer across increasing file sizes under moderate network conditions. For the uncompressed method, latency rises sharply from 910 ms at 100 MB to 7350 ms at 900 MB, reflecting the high bandwidth demand of transmitting raw data. Larger files occupy the network for longer durations, which increases congestion and delays. In contrast, the compressed method consistently shows lower transfer times, increasing from 520 ms to 3720 ms over the same range. By reducing payload size before transmission, compression lowers network utilization and shortens completion time. Although additional processing is required for encoding and decoding, the reduction in communication overhead provides a net performance gain. The growing difference between the two approaches demonstrates that compression becomes more effective as file size increases. Overall, compressed transfer offers better efficiency and scalability in distributed environments.

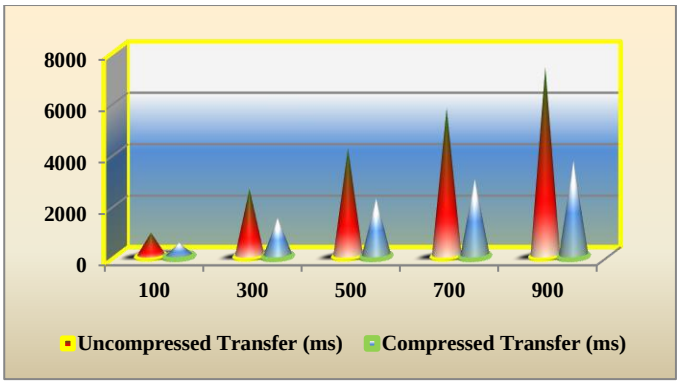

Fig 10. Uncompressed Vs Compressed Transfer – 2

Fig 10. The graph compares transfer time between Uncompressed Transfer and Compressed Transfer as file size increases from 100 MB to 900 MB under moderate network conditions. The uncompressed line rises steeply from 910 ms to 7350 ms, indicating significant growth in delay due to high bandwidth consumption. In contrast, the compressed line increases more gradually from 520 ms to 3720 ms because reduced payload sizes enable faster transmission. The widening gap between the two curves shows the clear advantage of compression. Overall, the graph highlights improved efficiency, lower latency, and better scalability with compressed transfer.

Table IX. Uncompressed Vs Compressed Transfer – 3

File Size (MB)	Uncompressed Transfer (ms)	Compressed Transfer (ms)
100	1050	610
300	2980	1710
500	4800	2580
700	6550	3430
900	8400	4250

Table IX Compares transfer time between Uncompressed Transfer and Compressed Transfer across increasing file sizes under heavy network conditions. The uncompressed approach shows a sharp rise in latency from 1050 ms at 100 MB to 8400 ms at 900 MB, indicating substantial bandwidth consumption and prolonged transmission delays. Larger files occupy the network for extended periods, which increases congestion and slows overall performance. In contrast, the compressed approach demonstrates significantly lower transfer times, increasing from 610 ms to 4250 ms. By reducing the volume of transmitted data, compression lowers network utilization and shortens completion time even during high traffic. Although compression introduces processing overhead, the reduction in communication cost results in a net performance benefit. The widening difference between the two methods highlights the effectiveness of compression. Overall, compressed transfer provides better efficiency, improved scalability, and more stable performance in distributed environments.

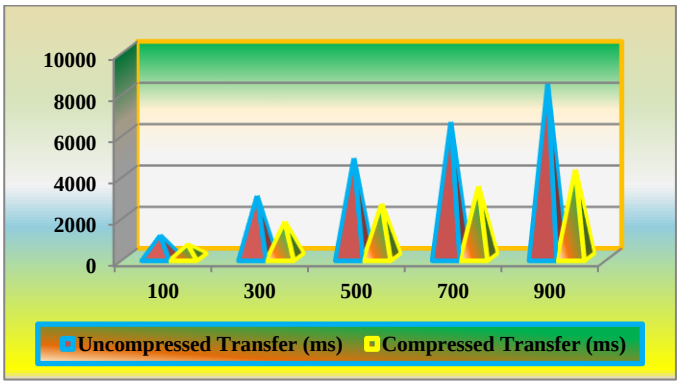

Fig 11. Uncompressed Vs Compressed Transfer – 3

Fig 11. The graph compares transfer time between Uncompressed Transfer and Compressed Transfer as file size increases from 100 MB to 900 MB under heavy network conditions. The uncompressed curve rises sharply from 1050 ms to 8400 ms, reflecting high bandwidth consumption and significant transmission delays. In contrast, the compressed curve increases more gradually from 610 ms to 4250 ms due to reduced payload size. The gap between the two lines widens as file size grows, demonstrating that compression becomes increasingly beneficial for larger transfers. Overall, the graph highlights improved efficiency, lower latency, and better scalability with compressed transfer.

EVALUATION

The evaluation analyzes transfer time for Uncompressed Transfer and Compressed Transfer across varying file sizes and network conditions. Measurements show that uncompressed transmission leads to steadily increasing latency as data volume grows, primarily due to higher bandwidth consumption and network congestion. In contrast, compressed transfer consistently reduces completion time by lowering the amount of data transmitted. Although compression introduces processing overhead, the reduction in communication delay provides an overall performance gain. The advantage becomes more significant for medium and large files. These results confirm that compression improves bandwidth utilization, shortens transfer duration, and enhances scalability in distributed environments.

CONCLUSION

Efficient data transfer is essential for maintaining performance and scalability in distributed systems where large volumes of information are exchanged frequently. Conventional uncompressed transfer methods consume significant bandwidth and lead to steadily increasing latency as file sizes and concurrency grow. This behavior results in network congestion, longer completion times, and reduced overall efficiency. In contrast, compressed transfer reduces payload size and improves bandwidth utilization, leading to faster transmission and more stable performance. Despite the additional processing overhead, the overall transfer time remains lower, particularly for medium and large files. The observed improvements demonstrate that intelligent use of compression enhances resource efficiency and supports scalable data movement. Addressing transfer inefficiencies is therefore critical for reliable and high performance distributed environments.

Future Work: Future work will focus on reducing memory overhead by introducing lightweight buffering techniques, dynamic memory allocation, and efficient temporary storage management to minimize resource consumption while maintaining stable and efficient transfer performance.

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